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# 19

## State Estimation

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An online AC power flow is a valuable application when determining the critical elements affecting power system operation and control such as overloaded lines, credible contingencies, and unsatisfactory voltages. It is the basis for any real-time security assessment and enhancement applications.

AC power flow algorithms calculate real and reactive line flows based on a multitude of inputs with generator bus voltages, real power bus injections, and reactive power bus injections being a partial list. This implies that in order to calculate the line flows using a power flow algorithm, all of the input information (voltages, real power injections, reactive power injections, etc.) must be known *a priori* to the algorithm being executed.

An obvious way to implement an online AC power flow is to telemeter the required input information at every location in the power system. This would require not only a large number of **remote terminal units** (RTUs), but also an extensive communication infrastructure to telemeter the data to the **SCADA** system, both of which are costly. Although the generator bus voltages are usually readily available, the injection data is frequently what is lacking. This is because it is much easier and cheaper to monitor the net injection at a bus than to measure separate injections directly.

Also, this approach presents weaknesses for the online AC power flow that are due to meter accuracy and communication failure. An online power flow relying on a specific set of measurements could become unusable or give erroneous results if any of the predefined measurements became unavailable due to communication failure or due to misoperation of measurement devices. This is not a desirable outcome of an online application designed to alert system operators to unsecure conditions.

Given the above obstacles of utilizing an online AC power flow, work was conducted in the late 1960s and early 1970s (Schweppe and Wildes, Jan. 1970) into developing a process of performing an online power flow using not just the limited data needed for the classical AC power flow algorithm, but using all available measurements. This work led to the **state estimator**, which uses not only the aforementioned voltages but other telemetered measurements such as real and reactive line flows, circuit breaker statuses, and transformer tap settings.

### 19.1 State Estimation Problem

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State estimators perform a statistical analysis using a set of  $m$  imperfect redundant data telemetered from the power system to determine the state of the system. The state of the system is a function of  $n$

**state variables:** bus voltages and relative phase angles, and tap changing transformer positions. Although the state estimation solution is not a “true” representation of the system, it is the “best” possible representation based on the telemetered measurements.

Also, it is necessary to have the number of measurements greater than the number of states ( $m \geq n$ ) to yield a representation of the complete state of the system. This is known as the observability criterion. Typically,  $m$  is two to three times the value of  $n$ , allowing for a considerable amount of redundancy in the measurement set.

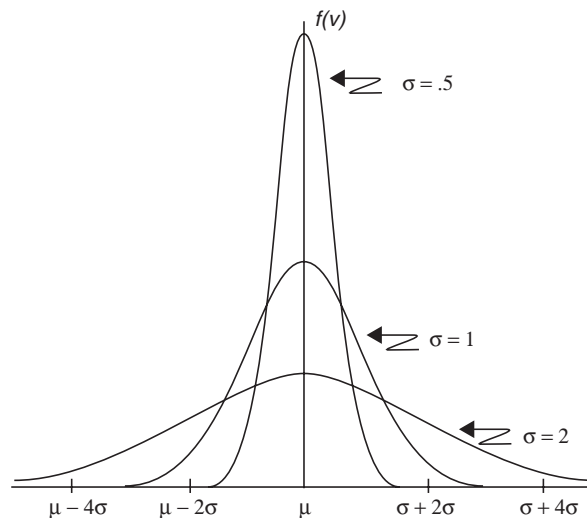
### 19.1.1 Underlying Assumptions

Telemetered measurements usually are corrupted since they are susceptible to noise. Even when great care is taken to ensure accuracy, unavoidable random noise enters into the measurement process, which distorts the telemetered values.

Fortunately, statistical properties associated with the measurements allow certain assumptions to be made to estimate the true measured value. First, it is assumed the measurement noise has an expected value, or average, of zero. This assumption implies the error in each measurement has equal probability of taking on a positive or negative value. It is also assumed that the expected value for the square of the measurement error is normal and has a standard deviation of  $\sigma$ , and the correlation between measurements is zero (i.e., independent).<sup>1</sup> A variable is said to be normal (or Gaussian) if its probability density function has the form

$$f(v) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{v^2}{2\sigma^2}}. \quad (19.1)$$

This distribution is also known as the bell curve due to its symmetrical shape resembling a bell as can be seen in Fig. 19.1. The normal distribution is used for the modeling of measurement errors since it is the distribution that results when many factors contribute to the overall error.



**FIGURE 19.1** Normal probability distribution curve with a mean of  $\mu$ .

<sup>1</sup>In practice, measurements  $i$  and  $j$  are not necessarily independent since one measurement device may measure more than one value. Therefore, if the measurement device is bad, probably both measurements  $i$  and  $j$  are bad also.

Figure 19.1 also illustrates the effect of standard deviation on the normal density function. Standard deviation,  $\sigma$ , is a measure of the spread of the normal distribution about the mean ( $\mu$ ) and gives an indication of how many samples fall within a given interval around the mean. A large standard deviation implies there is a high probability the measurement noise will take on large values. Conversely, a small standard deviation implies there is a high probability the measurement noise will take on small values.

### 19.1.2 Measurement Representations

Since a measurement is not exact, it can be expressed with an error component of the form

$$z = z_T + v \quad (19.2)$$

where  $z$  is the measured value,  $z_T$  is the true value, and  $v$  is the measurement error that represents uncertainty in the measurement. In general, the measured value, as expressed in Eq. (19.2), can be related to the states,  $x$ , by

$$z = h(x) + v \quad (19.3)$$

where  $h(x)$  is a vector of nonlinear functions relating the measurements to the state variables. An example of the  $h(x)$  vector can be shown using the transmission line in Fig. 19.2.

Assuming real and reactive power measurements are being made at bus  $i$  in Fig. 19.2, the equations for line flow from bus  $i$  to  $j$  need to be determined as

$$P_{ij} = |\tilde{V}_i|^2 (g_{ij} + g_{i_{sh}}) - |\tilde{V}_i| |\tilde{V}_j| [g_{ij} \cos(\delta_{ij}) + b_{ij} \sin(\delta_{ij})] \quad (19.4)$$

$$Q_{ij} = -|\tilde{V}_i|^2 (b_{ij} + b_{i_{sh}}) - |\tilde{V}_i| |\tilde{V}_j| [g_{ij} \sin(\delta_{ij}) - b_{ij} \cos(\delta_{ij})] \quad (19.5)$$

where  $|\tilde{V}_i|$  is the magnitude of the voltage at bus  $i$ ,  $|\tilde{V}_j|$  is the magnitude of the voltage at bus  $j$ ,  $\delta_{ij}$  is the phase angle difference between bus  $i$  and bus  $j$ ,  $g_{ij}$  and  $b_{ij}$  are the conductance and susceptance of line  $i$ - $j$ , respectively, and  $g_{i_{sh}}$  and  $b_{i_{sh}}$  are the shunt conductance and susceptance at bus  $i$ , respectively.

Using Eqs. (19.4) and (19.5), Eq. (19.3) can now be rewritten as<sup>2</sup>

$$\begin{aligned} \bar{z} &= \bar{h}(x) + \bar{v} \\ &= \begin{bmatrix} |\tilde{V}_i|^2 (g_{ij} + g_{i_{sh}}) - |\tilde{V}_i| |\tilde{V}_j| [g_{ij} \cos(\delta_{ij}) + b_{ij} \sin(\delta_{ij})] \\ -|\tilde{V}_i|^2 (b_{ij} + b_{i_{sh}}) - |\tilde{V}_i| |\tilde{V}_j| [g_{ij} \sin(\delta_{ij}) - b_{ij} \cos(\delta_{ij})] \end{bmatrix} + \begin{bmatrix} v_{P_{ij}} \\ v_{Q_{ij}} \end{bmatrix} \end{aligned} \quad (19.6)$$

which expresses the measurements entirely in terms of network parameters (which are assumed known) and system states (bus voltage and phase angle).

### 19.1.3 Solution Methods

The solution to the state estimation problem has been addressed by a broad class of techniques (Filho et al., Aug. 1990) and differs from power flow algorithms in two modes:

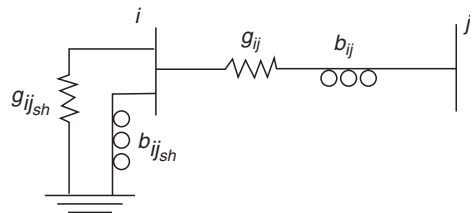


FIGURE 19.2 Transmission line representation.

<sup>2</sup>The superscript  $\bar{\cdot}$  represents a vector.

1. certain input data are either missing or inexact, and/or
2. the algorithm used for the calculation may entail approximations and approximate methods designed for high speed processing in the online environment.

In this section, two different solution methods to the state estimation problem will be introduced and described.

### 19.1.3.1 Weighted Least Squares

The most common approach to solving the state estimation problem is using the method of weighted least squares (WLS). This is accomplished by identifying the values of the state variables that minimize the performance index,  $J$  (the weighted sum of square errors):

$$J = \bar{e}^T R^{-1} \bar{e} \quad (19.7)$$

where the weighting factor,  $R$ , is the diagonal covariance matrix of the measurements and is defined as

$$E[\bar{v}\bar{v}^T] = R = \begin{bmatrix} \sigma_1^2 & 0 & 0 & 0 & 0 \\ 0 & \sigma_2^2 & 0 & 0 & 0 \\ 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & 0 & \cdots & 0 \\ 0 & 0 & 0 & 0 & \sigma_m^2 \end{bmatrix}. \quad (19.8)$$

By defining the error,  $e$ , in Eq. (19.7) as the difference between the true measured value,  $z$ , and the estimated measured value,  $\hat{z}$ ,

$$\bar{e} = \bar{z} - \hat{\bar{z}} \quad (19.9)$$

a new form for the performance index can be written as

$$J = (\bar{z} - \bar{h}(x))^T R^{-1} (\bar{z} - \bar{h}(x)) \quad (19.10)$$

As shown in Eqs. (19.8) and (19.10), the weights are defined by the inverse of the measurements variances. As a result, measurements of a higher quality have smaller variances that correspond to their weights having higher values, while measurements with poor quality have smaller weights due to the correspondingly higher variance values.

In order to minimize the performance index,  $J$ , a first-order necessary condition must hold, namely:

$$\left. \frac{\partial J}{\partial \bar{x}} \right|_{x^k} = 0 \quad (19.11)$$

Evaluating Eq. (19.10) at the necessary condition gives the following:

$$H(x^k)^T R^{-1} (\bar{z} - \bar{h}(x)) = 0 \quad (19.12)$$

where  $H(x)$  represents the  $m \times n^3$  measurement Jacobian matrix evaluated at iteration  $k$ :

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<sup>3</sup> $m$  represents the number of measurements;  $n$  represents the number of states.

$$H(x) = \left[ \begin{array}{cccc} \frac{\partial h_1}{\partial x_1} & \frac{\partial h_1}{\partial x_2} & \cdots & \frac{\partial h_1}{\partial x_n} \\ \frac{\partial h_2}{\partial x_1} & \frac{\partial h_2}{\partial x_2} & \cdots & \frac{\partial h_2}{\partial x_n} \\ \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots \\ \frac{\partial h_m}{\partial x_1} & \frac{\partial h_m}{\partial x_2} & \cdots & \frac{\partial h_m}{\partial x_n} \end{array} \right]_{x^k} \quad (19.13)$$

A linearized relationship between the measurements and the state variables is then found by expanding the Taylor series expansion of the function  $\bar{h}(x)$  around a point  $x^k$ :

$$\bar{h}(x^k) = \bar{h}(x^k) + \Delta \bar{x}^k \frac{\partial \bar{h}(x^k)}{\partial \bar{x}} + \text{higher order terms.} \quad (19.14)$$

This set of equations can be solved using an iterative approach such as Newton Raphson's method. At the  $(k+1)^{\text{th}}$  iteration, the refreshed values of the state variables can be obtained from their values in the previous iteration by:

$$\bar{x}^{k+1} = \bar{x}^k + \left( H(x^k)^T R^{-1} H(x^k) \right)^{-1} H(x^k)^T R^{-1} (\bar{z} - \bar{h}(x^k)). \quad (19.15)$$

At convergence, the solution  $\bar{x}^{k+1}$  corresponds to the weighted least squares estimates of the state variables. Convergence can be determined either by satisfying

$$\max(\bar{x}^{k+1} - \bar{x}^k) \leq \varepsilon \quad (19.16)$$

or

$$J^{k+1} - J^k \leq \varepsilon \quad (19.17)$$

where  $\varepsilon$  is some predetermined convergence factor.

### 19.1.3.2 Linear Programming

Another solution method that addresses the state estimation problem is linear programming. Linear programming is an optimization technique that serves to minimize a linear objective function subject to a set of constraints:

$$\begin{aligned} & \min \{ \bar{c}^T \bar{x} \} \\ & s.t. \ A \bar{x} = \bar{b} \\ & \quad \bar{x} \geq 0 \end{aligned} \quad (19.18)$$

There are many different techniques associated with solving linear programming problems including the simplex and interior point methods.

Since the objective function, as expressed in Eq. (19.10), is quadratic in terms of the unknowns (states), it must be rewritten in a linear form. This is accomplished by first rewriting the measurement error, as expressed in Eq. (19.3), in terms of a positive measurement error,  $v_p$ , and a negative measurement error,  $v_n$ :

$$\begin{aligned}\bar{z} &= \bar{h}(x) + \bar{v} \\ &= \bar{h}(x) + \bar{v}_p - \bar{v}_n\end{aligned}\tag{19.19}$$

Restricting the positive and negative measurement errors to only nonnegative values insures the problem is bounded. This was not a concern in the weighted least squares approach since a quadratic function is convex and is guaranteed to contain a global minimum.

Using the new definition of a measurement described in Eq. (19.19) and the inverse of the diagonal covariance matrix of the measurements for weights as described in the weighted least squares approach, the objective function can now be written as:

$$J = R^{-1}(\bar{v}_p + \bar{v}_n)\tag{19.20}$$

The constraints are the equations relating the state vector to the measurements as shown in Eq. (19.19). Once again, since  $h(x)$  is nonlinear, it must be linearized around a point  $x^k$  by expanding the Taylor series, as was performed previously in the weighted least squares approach. The solution to the state estimation problem can then be determined by solving the following linear program:

$$\begin{aligned}\min & \left\{ R^{-1}(\bar{v}_p + \bar{v}_n) \right\} \\ \text{s.t. } & \Delta \bar{z}^k - H(x^k) \Delta x^k + \bar{v}_p - \bar{v}_n = 0 \\ & \bar{v}_p \geq 0 \\ & \bar{v}_n \geq 0\end{aligned}\tag{19.21}$$

where  $H(x^k)$  represents the  $m \times n$  measurement Jacobian matrix evaluated at iteration  $k$  as defined in Eq. (19.13).

## 19.2 State Estimation Operation

State estimators are typically executed either periodically (i.e., every 5 min), on demand, or due to a status change such as a breaker operation isolating a line section. To illustrate the relationship of the state estimator with respect to other EMS applications, a simple depiction of an EMS is shown below in Fig. 19.3:

As shown, the state estimator receives inputs from the supervisory control and data acquisition (SCADA) system and the network topology assessment applications and stores the state of the system in a central location (i.e., database). Power system applications, such as contingency analysis and optimal power flow, can then be executed based on the state of the system as computed by the state estimator.

### 19.2.1 Network Topology Assessment

Before the state estimator is executed in realtime, the topology of the network is determined. This is accomplished by a system or **network configurator** that establishes the configuration of the power system network based on telemetered breaker and switch statuses. The network configurator normally addresses questions like:

- Have breaker operations caused individual buses to either be split into two or more isolated buses, or combined into a single bus?
- Have lines been opened or restored to service?

The state estimator then uses the network determined by the network configurator, which consists only of energized (online) lines and devices, as a basis for the calculations to determine the state of the system.

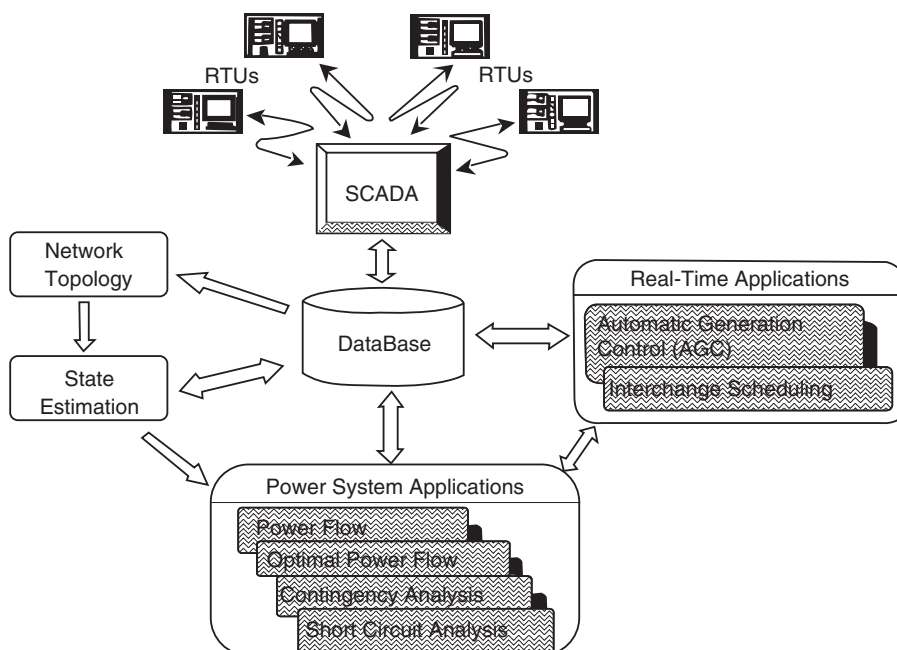


FIGURE 19.3 Simple depiction of an EMS.

## 19.2.2 Error Identification

Since state estimators utilize telemetered measurements and network parameters as a foundation for their calculations, the performance of the state estimator depends on the accuracy of the measured data as well as the parameters of the network model. Fortunately, the use of all available measurements introduces a favorable secondary effect caused by the redundancy of information. This redundancy provides the state estimator with more capabilities than just an online AC power flow; it introduces the ability to detect “bad” data. Bad data can come from many sources, such as:

- approximations,
- simplified model assumptions,
- human data handling errors, or
- measurement errors due to faulty devices (e.g., transducers, current transformers).

### 19.2.2.1 Telemetered Data

The ability to detect and identify bad measurements is an extremely useful feature of the state estimator. Without the state estimator, obviously wrong telemetered measurements would have little chance of being identified. With the state estimator, operation personnel can have a greater confidence that telemetered data is not grossly in error.

Data is tagged as “bad” when the estimated value is unreasonably different from the measured/telemetered value obtained from the RTU. As a simple example, suppose a bus voltage is measured to be 1.85 pu and is estimated to be 0.95 pu. In this case, the bus voltage measurement could be tagged as bad. Once data is tagged as bad, it should be removed from the measurement set before being utilized by the state estimator.

Most state estimators rely on a combination of preestimation and postestimation schemes for detection and elimination of bad data. Preestimation involves gross bad data detection and consistency tests. Data is identified as bad in preestimation by the detection of gross measurement errors such as



zero voltages or line flows that are outside reasonable limits using network topology assessment. Consistency tests classify data either as valid, suspect, or raw for use in postestimation analysis by using statistical properties of related measurements. Measurements are classified as valid if they pass a consistency test that separates measurements into subsets based on a consistency threshold. If the measurement fails the consistency test, it is classified as suspect. Measurements are classified as raw if a consistency test cannot be made and they cannot be grouped into any subset. Raw measurements typically belong to nonredundant portions of the complete measurement set.

Postestimation involves performing a statistical analysis (e.g., hypothesis testing using chi-square tests) on the normalized measurement residuals. A normalized residual is defined as

$$r_i = \frac{z_i - h_i(x)}{\sigma_i} \quad (19.22)$$

where  $\sigma_i$  is the  $i$ -th diagonal term of the covariance matrix,  $R$ , as defined in Eq. (19.8). Data is identified as bad in postestimation typically when the normalized residuals of measurements classified as suspect lie outside a predefined confidence interval (i.e., fail the chi-square test).

### 19.2.2.2 Parameter Data

In parameter error identification, network parameters (i.e., admittances) that are suspicious are identified and need to be estimated. The use of faulty network parameters can severely impact the quality of state estimation solutions and cause considerable error. A requirement for parameter estimation is that all parameters be identifiable by measurements. This requirement implies the lines under consideration have associated measurements, thereby increasing the size of the measurement set by  $l$ , where  $l$  is the number of parameters to be estimated. Therefore, if parameter estimation is to be performed, the observability criterion must be augmented to become  $m \geq n + l$ .

## 19.2.3 Unobservability

By definition, a state variable is unobservable if it cannot be estimated. Unobservability occurs when the observability criterion is violated ( $m < n$ ) and there are insufficient redundant measurements to determine the state of the system. Mathematically, the matrix  $H(x^k)^T R^{-1} H(x^k)$  of Eq. (19.15) becomes singular and cannot be inverted.

The obvious solution to the unobservability problem is to increase the number of measurements. The problem then becomes where and how many measurements need to be added to the measurement set. Adding additional measurements is costly since there are many supplementary factors that must be addressed in addition to the cost of the measuring device such as RTUs, communication infrastructure, and software data processing at the EMS. A number of approaches have been suggested that try to minimize the cost while satisfying the observability criterion (Baran et al., Aug. 1995; Park et al., Aug. 1998).

Another solution to address the problem of unobservability is to augment the measurement set with pseudomeasurements to reach an observability condition for the network. When adding pseudomeasurements to a network, the equation of the pseudomeasured quantity is substituted for actual measurements. In this case, the measurement covariance values in Eq. (19.8) associated with these measurements should have large values that allow the state estimator to treat the pseudomeasurements as if they were measured from a very poor metering device.

## 19.3 Example State Estimation Problem

This section provides a simple example to illustrate how the state estimation process is performed. The WLS method, as previously described, will be applied to a sample system.

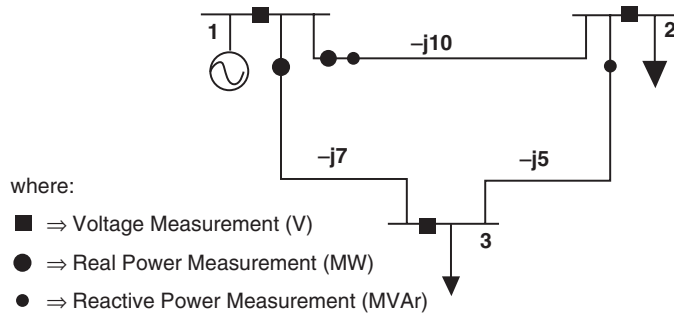


FIGURE 19.4 Sample three-bus power flow system.

### 19.3.1 System Description

A sample three-bus system is shown in Fig. 91.4.

Bus 1 is assumed to be the reference bus with a corresponding angle of zero. All other relevant system data is given in Table 19.1.

### 19.3.2 WLS State Estimation Process

First, the states ( $x$ ) are defined as the angles at bus 2 and bus 3 and the voltage magnitudes at all buses<sup>4</sup>:

$$\bar{x} = \begin{bmatrix} \delta_2 \\ \delta_3 \\ |\tilde{V}_1| \\ |\tilde{V}_2| \\ |\tilde{V}_3| \end{bmatrix}$$

This gives a total of seven measurements and five states that satisfy the observability criterion requiring more measurements than states.

Using the previously defined equations for the WLS state estimation procedure, the following can be determined:

TABLE 19.1 Sample System Data

| Measurement Type | Measurement Location | Measurement Value (pu) | Measurement Covariance ( $\sigma$ ) |
|------------------|----------------------|------------------------|-------------------------------------|
| $ \tilde{V} $    | Bus 1                | 1.02                   | 0.05                                |
| $ \tilde{V} $    | Bus 2                | 1.0                    | 0.05                                |
| $ \tilde{V} $    | Bus 3                | 0.99                   | 0.05                                |
| P                | Bus 1 – Bus 2        | 1.5                    | 0.1                                 |
| Q                | Bus 1 – Bus 2        | 0.2                    | 0.1                                 |
| P                | Bus 1 – Bus 3        | 1.0                    | 0.1                                 |
| Q                | Bus 2 – Bus 3        | 0.1                    | 0.1                                 |

<sup>4</sup>The angle at bus one is not chosen as a state since it is designated as the reference bus.

$$\begin{aligned}
R &= [\sigma_i^2] \\
&= \begin{bmatrix} (.05)^2 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & (.05)^2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & (.05)^2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & (.1)^2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & (.1)^2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & (.1)^2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & (.1)^2 \end{bmatrix} \\
\hat{\mathbf{z}} &= h(\bar{\mathbf{x}}) \\
&= \begin{bmatrix} x_3 \\ x_4 \\ x_5 \\ -10x_3x_4 \sin x_1 \\ 10x_3^2 - 10x_3x_4 \cos x_1 \\ -7x_3x_5 \sin x_2 \\ 5x_4^2 - 5x_4x_5 \cos(x_1 - x_2) \end{bmatrix} \\
H(x) &= \left[ \frac{\partial \hat{h}}{\partial \bar{\mathbf{x}}} \right] \\
&= \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ -10x_3x_4 \cos x_1 & 0 & -10x_4 \sin x_1 & -10x_3 \sin x_1 & 0 \\ 10x_3x_4 \sin x_1 & 0 & 20x_3 - 10x_4 \cos x_1 & -10x_3 \cos x_1 & 0 \\ 0 & -7x_3x_5 \cos x_2 & -7x_5 \sin x_2 & 0 & -7x_3 \sin x_2 \\ 5x_4x_5 \sin(x_1 - x_2) & -5x_4x_5 \sin(x_1 - x_2) & 0 & 10x_4 - 5x_5 \cos(x_1 - x_2) & -5x_4 \cos(x_1 - x_2) \end{bmatrix}
\end{aligned}$$

Using zero as an initial guess for the states representing voltage angles ( $x_1$  and  $x_2$ ) and the measured voltages as given in [Table 19.1](#) for the states representing voltage magnitudes ( $x_3$ ,  $x_4$ , and  $x_5$ ):

$$\begin{bmatrix} x_1^0 \\ x_2^0 \\ x_3^0 \\ x_4^0 \\ x_5^0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 1.02 \\ 1.00 \\ 0.99 \end{bmatrix},$$

the state values at the first iteration are determined by [Eq. \(19.15\)](#) to be

$$\begin{bmatrix} x_1^1 \\ x_2^1 \\ x_3^1 \\ x_4^1 \\ x_5^1 \end{bmatrix} = \begin{bmatrix} -0.147 \\ -0.142 \\ 1.022 \\ 1.003 \\ 0.984 \end{bmatrix}.$$

After four iterations, the state estimation process converges to the final states:

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} = \begin{bmatrix} -0.147 \\ -0.143 \\ 1.016 \\ 1.007 \\ 0.987 \end{bmatrix}.$$

Using the solved voltages and angles from the state estimation process, the line flows and bus injections can now be calculated. With the state of the system now known, other applications such as contingency analysis and optimal power flow may be performed. Notice, the state estimation process results in the state of the system, just as when performing a power flow but without *a priori* knowledge of bus injections.

## 19.4 Defining Terms

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**Remote Terminal Unit (RTU)**—Hardware that telemeters systemwide data from various field locations (i.e., substations, generating plants) to a central location.

**State estimator**—An application that uses a statistical process in order to estimate the state of the system.

**State variable**—The quantity to be estimated by the state estimator, typically bus voltage and angle.

**Network configurator**—An application that determines the configuration of the power system based on telemetered breaker and switch statuses.

**Supervisory Control and Data Acquisition (SCADA)**—A computer system that performs data acquisition and remote control of a power system.

**Energy Management System (EMS)**—A computer system that monitors, controls, and optimizes the transmission and generation facilities with advanced applications. A SCADA system is a subset of an EMS.

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